

Extratropical Transition: From Climatology to Prediction



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NASA GISS Seminar, September 12, 2018

Image: earth

```
from datetime import datetime, time

say_hi()
tell_them_what_you_are_going_to_tell_them()
introduce_ET()

main_topics = [ET_global_climatology, ET_stat_prediction]
for topic in main_topics:
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while datetime.now().time() < time(14):
    question = raw_input("Any questions?")
    try:
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Extratropical Transition (ET): A Primer



ET: A Primer



Cyclone Continuum

ET: A Primer

Cyclone Continuum



Tropical Cyclone

- Warm core
- Radially symmetric
- Fuel: Latent heat release

ET: A Primer

Cyclone Continuum



Tropical Cyclone

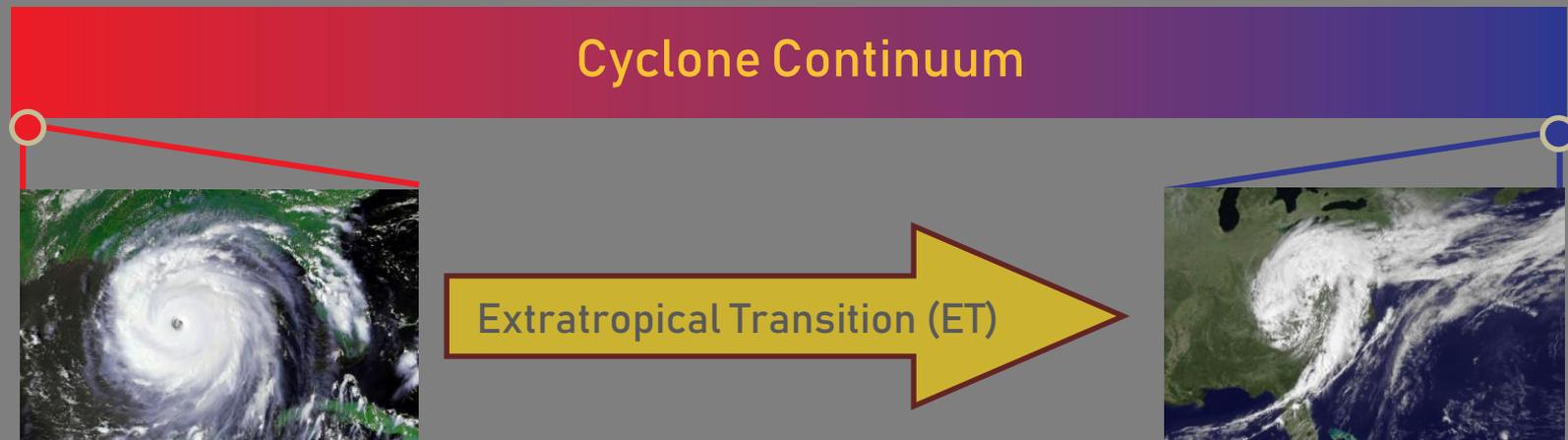
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Extratropical Cyclone

- Cold core
- Asymmetric (“comma”)
- Fuel: Baroclinicity

ET: A Primer



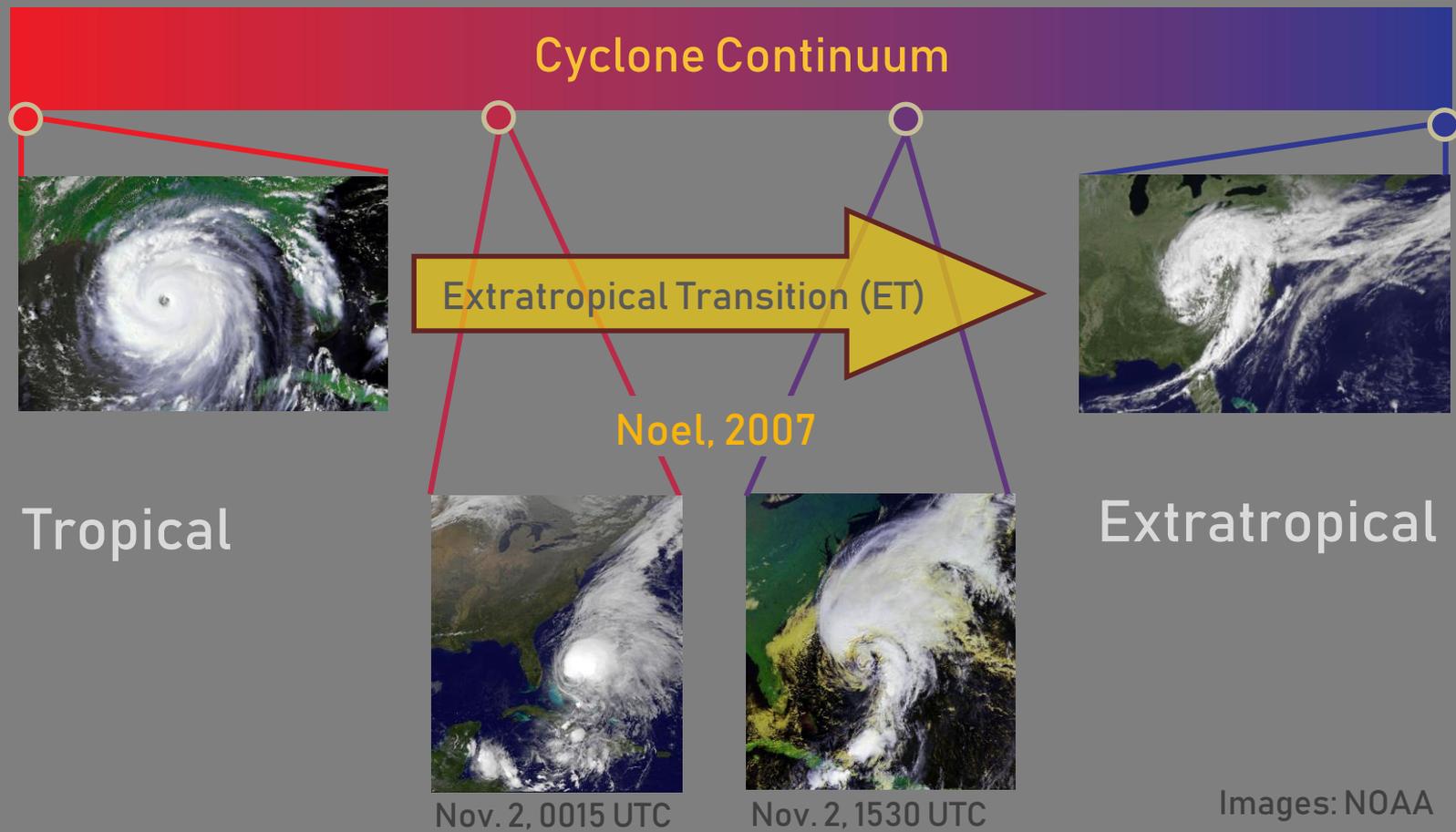
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ET: A Primer



Why do we care?



St. John's after Igor (2010)
Image: The Telegram



New York City after Sandy (2012)
Image: The Telegram



Global ET Climatology

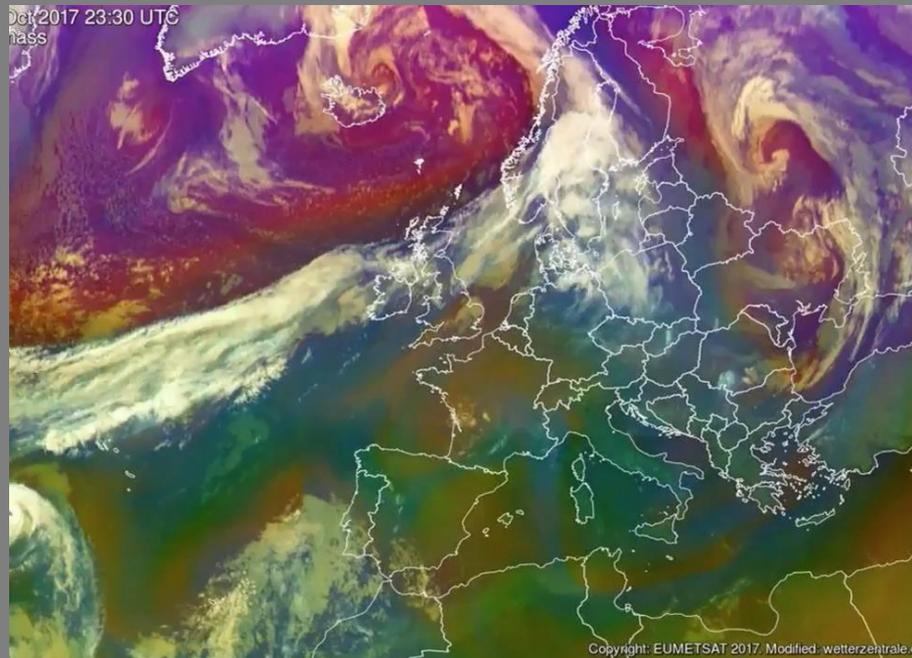
- Bieli et al. (2018) A Global Climatology of Extratropical Transition. Part I: Characteristics Across Basins (in review)
- Bieli et al. (2018) A Global Climatology of Extratropical Transition. Part II: Statistical Performance of the Cyclone Phase Space (in review)



From Case Studies...

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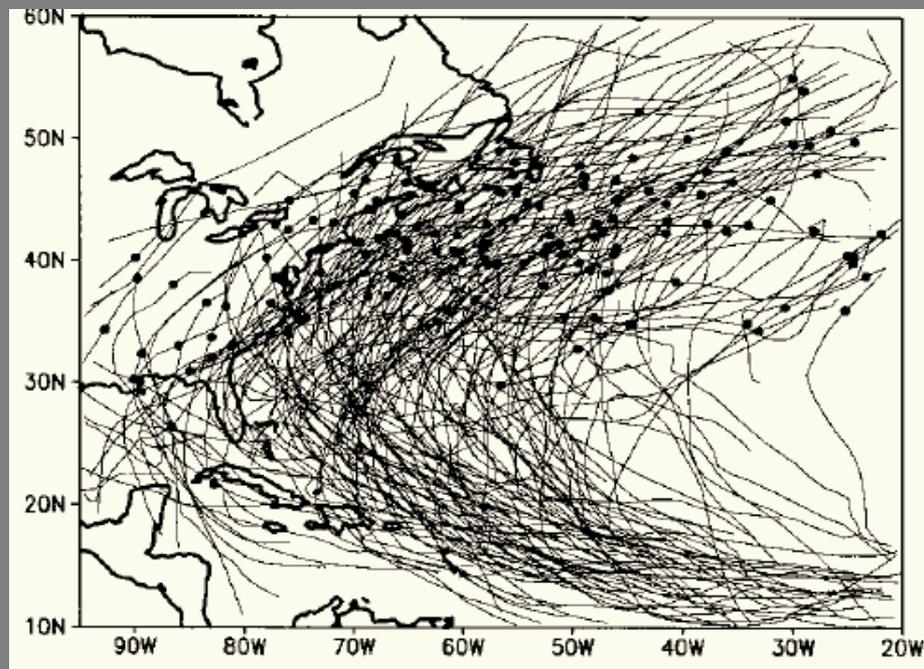
Ophelia (2017)



IR loop of Ophelia. Eumetsat/Wetterzentrale

....to Basins...

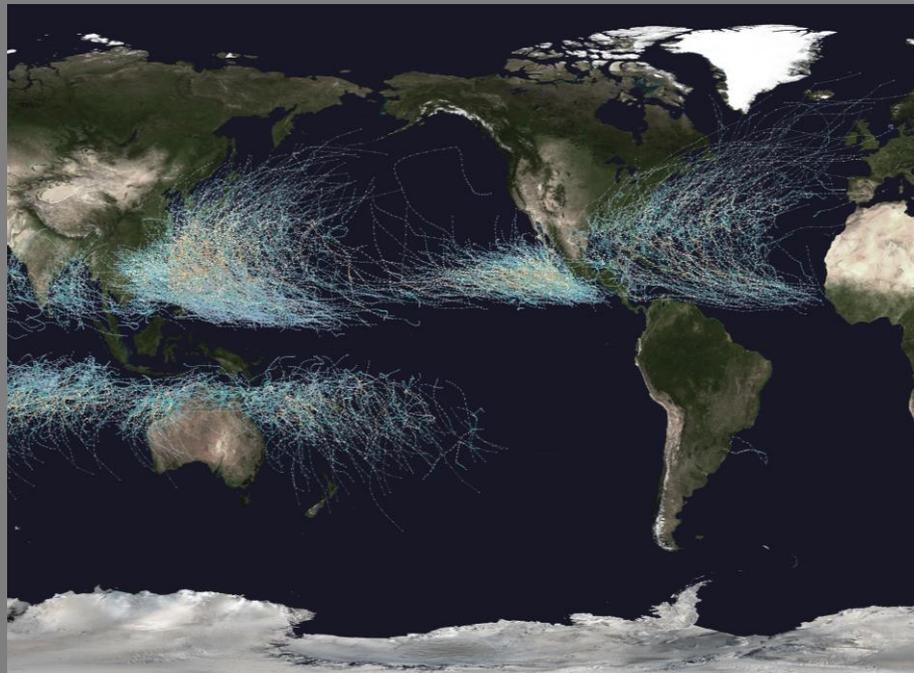
ET in the North Atlantic



ET in the Atlantic. Hart and Evans (2000)

...to a Global Climatology of ET

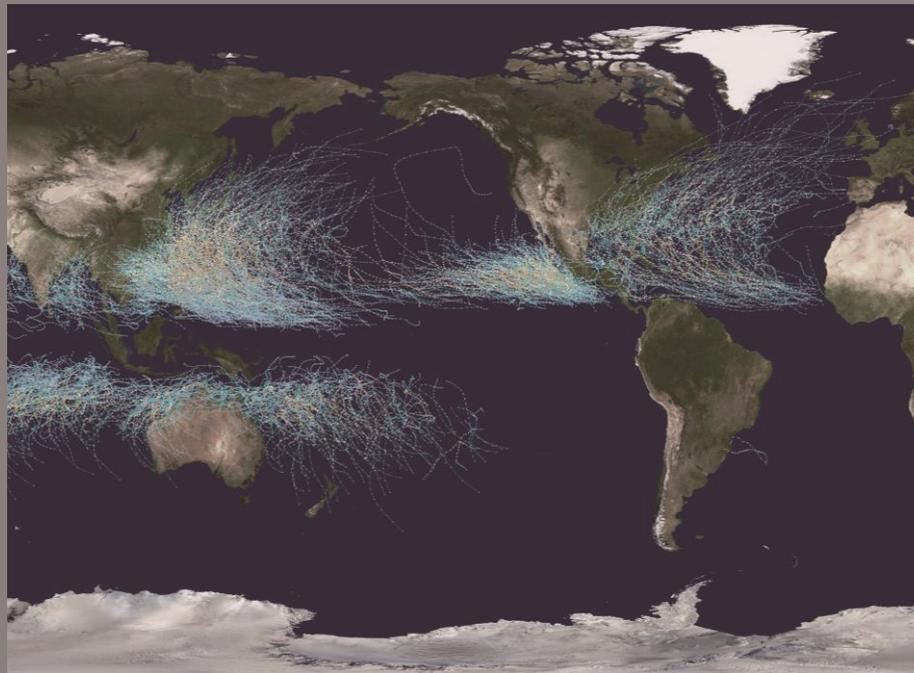
Global ET Climatology



Global TC tracks. Wikipedia

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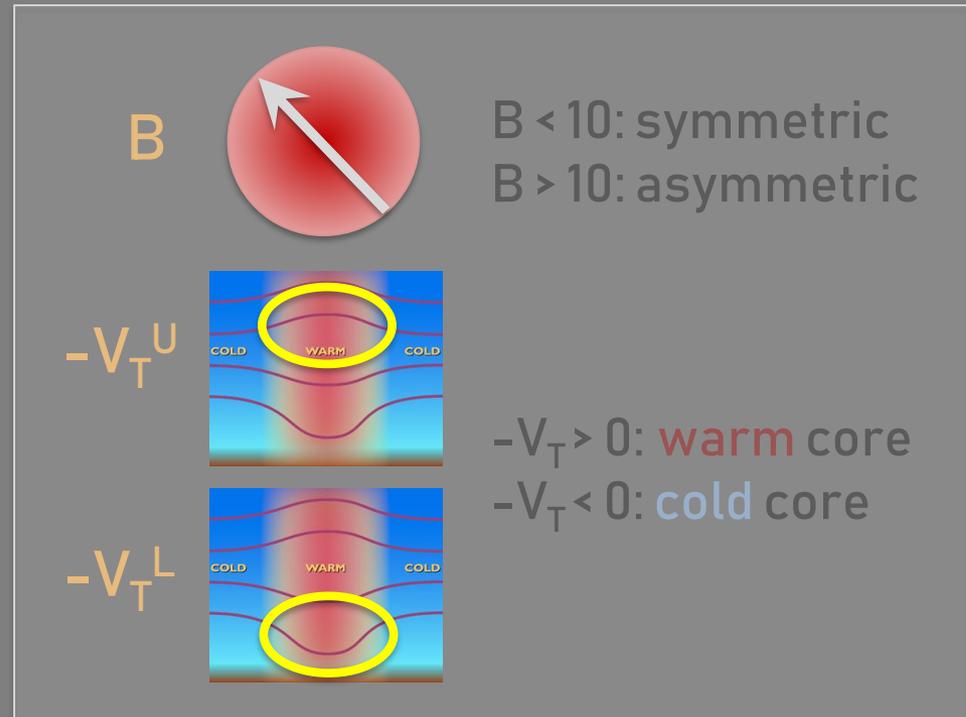
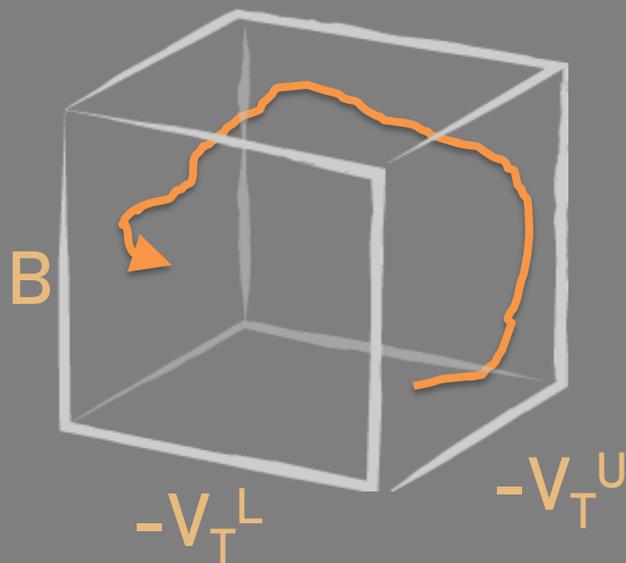


Global TC tracks. Wikipedia



Interlude: Measuring “(Extra)tropicalness” in the Cyclone Phase Space

Method: ET in the Cyclone Phase Space



$B < 10$: symmetric $B > 10$: asymmetric $-V_T > 0$: **warm** core $-V_T < 0$: **cold** core

ET in the Cyclone Phase Space

ET Onset

ET Completion

ET Pathway 1: $B \rightarrow V_T$

ET Pathway 2: $V_T \rightarrow B$

ET Pathway 3: **direct**

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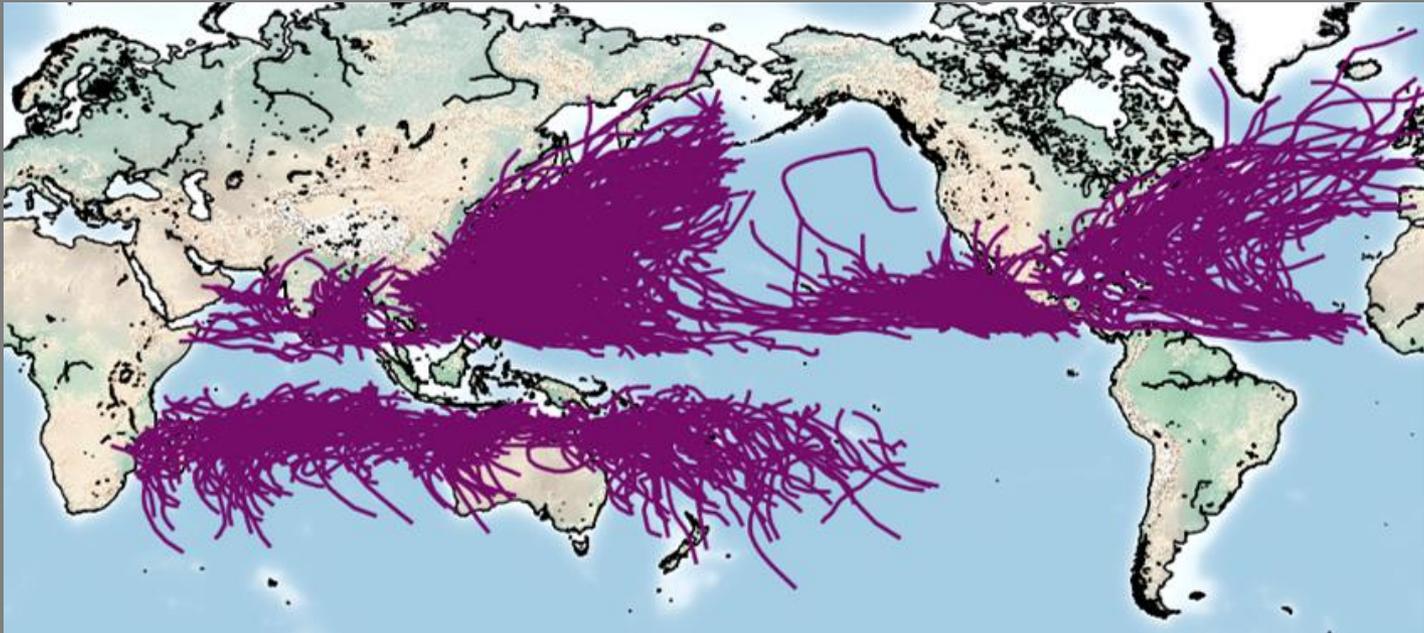


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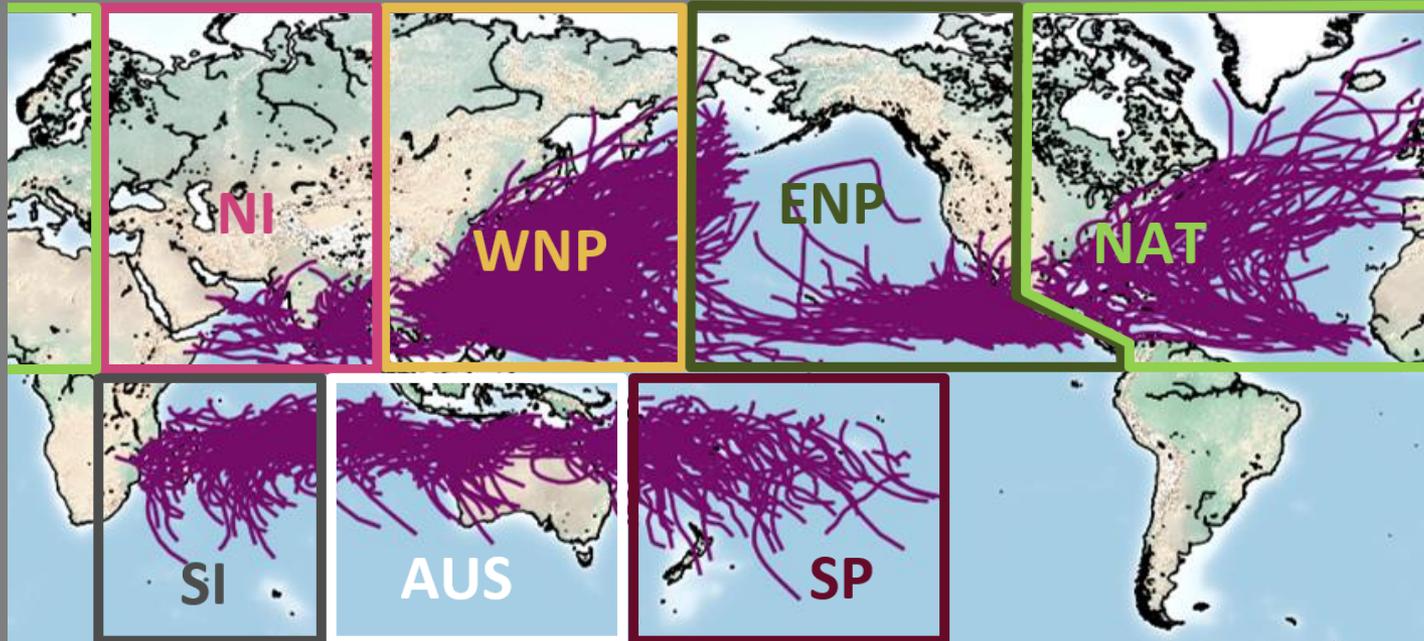
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Data: Best Tracks (1979–2017), Reanalyses



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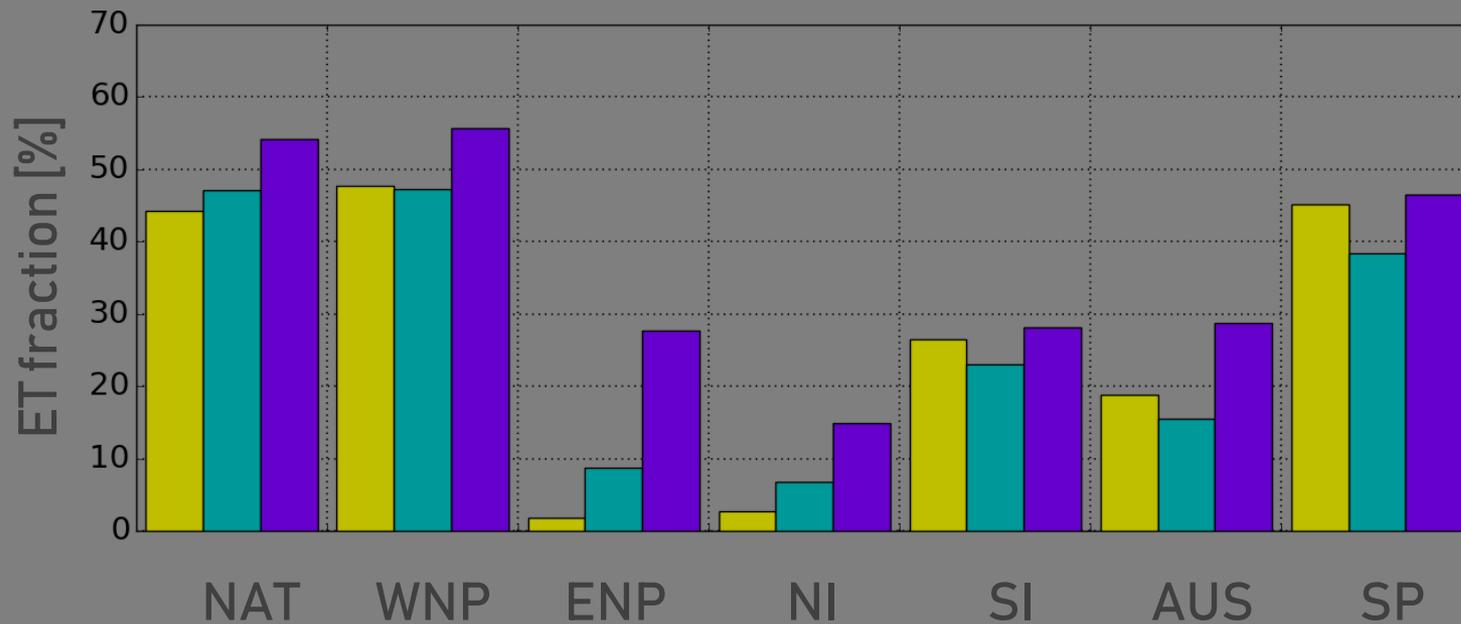


Global ET Climatology: Results

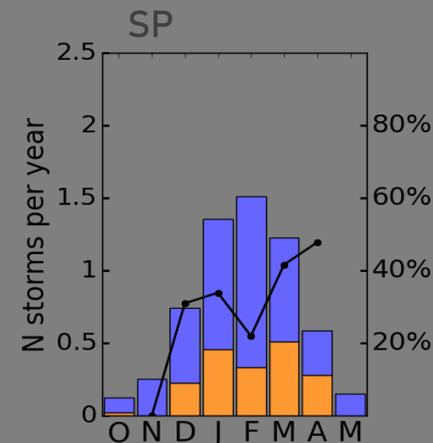
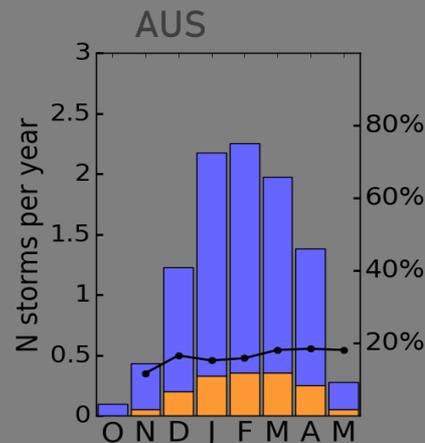
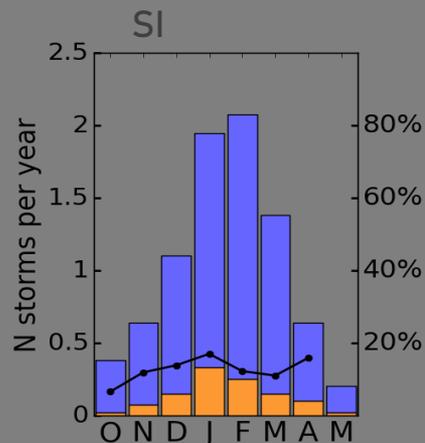
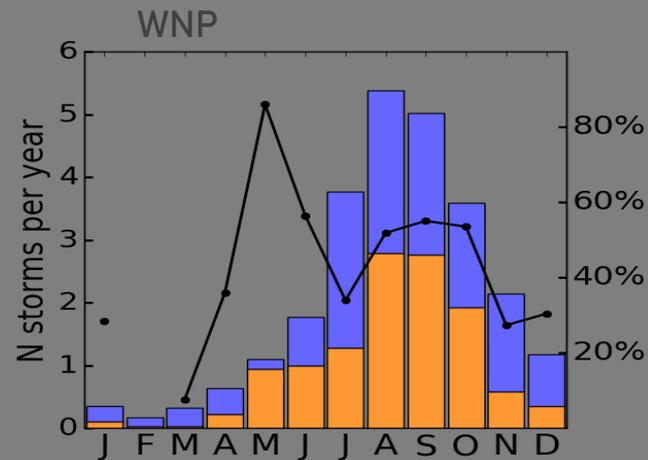
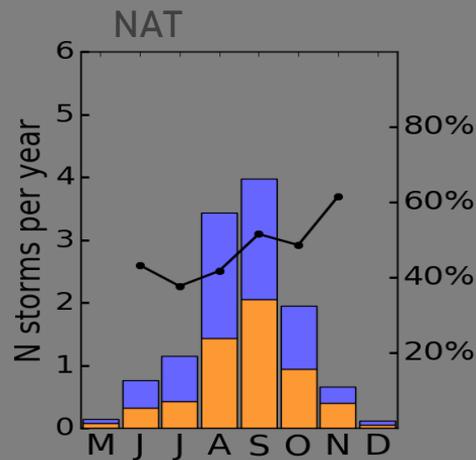
ET Fraction



- best-track labels
- CPS, JRA-55
- CPS, ERA-Interim

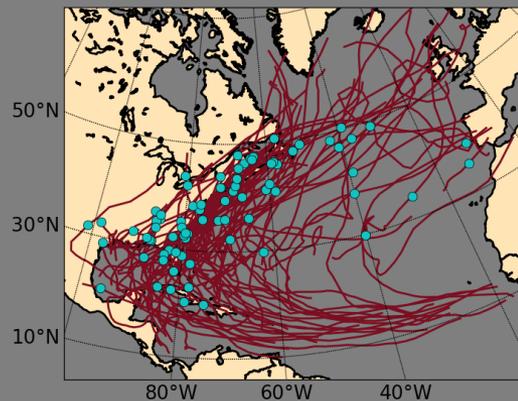


Seasonal Cycle

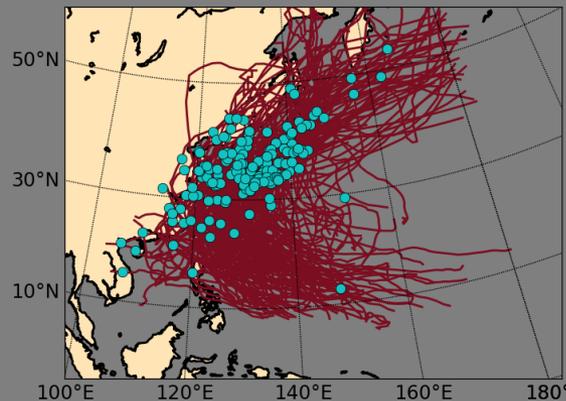


Landfalls of ET Storms

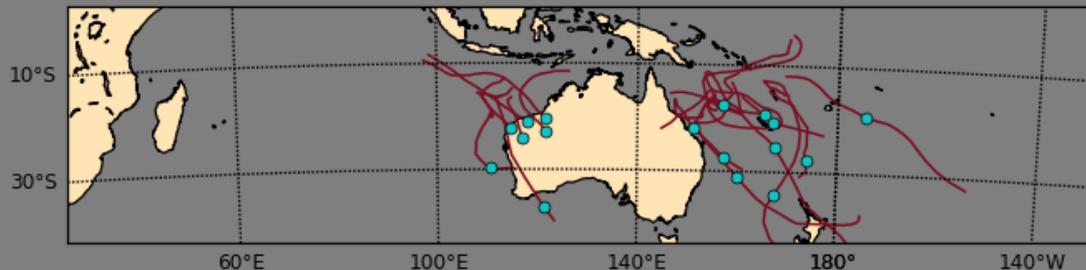
NAT



WNP



SH



 ET completion

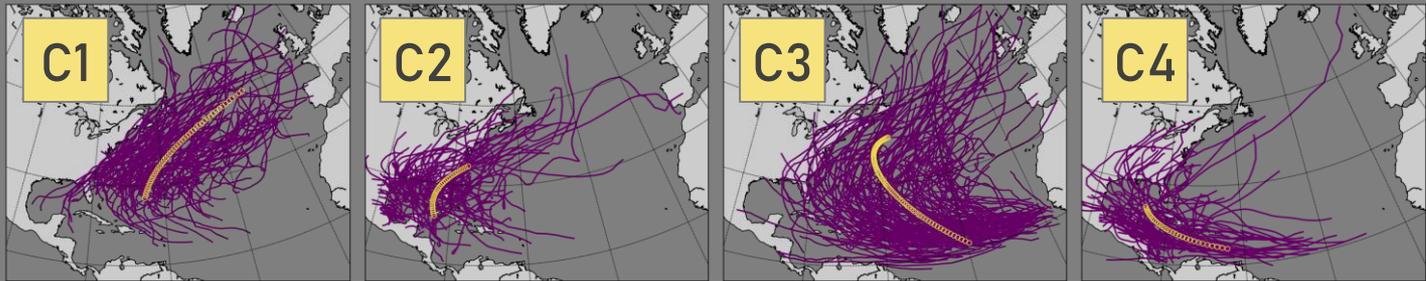
- Landfalls of transitioning or extratropical storms:
NAT: 3 -4 per year,
WNP: 7-10 per year
- SH: Landfalls by ET storms mainly affect AUS region, but at lower rate



Cluster Analysis

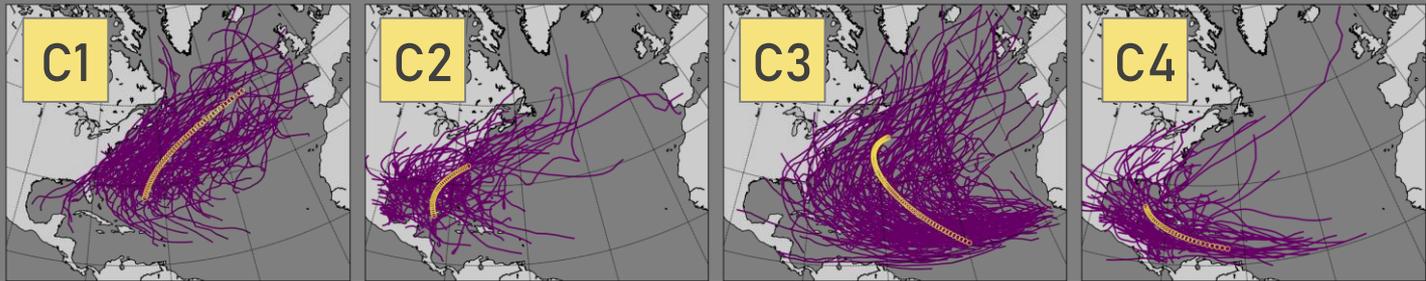
Cluster Analysis

NAT

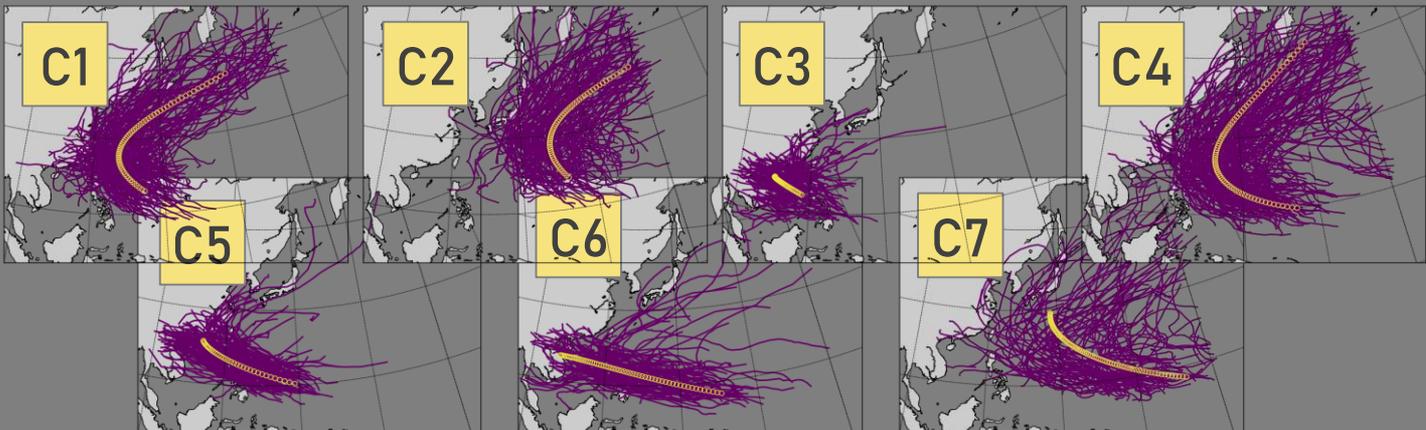


Cluster Analysis

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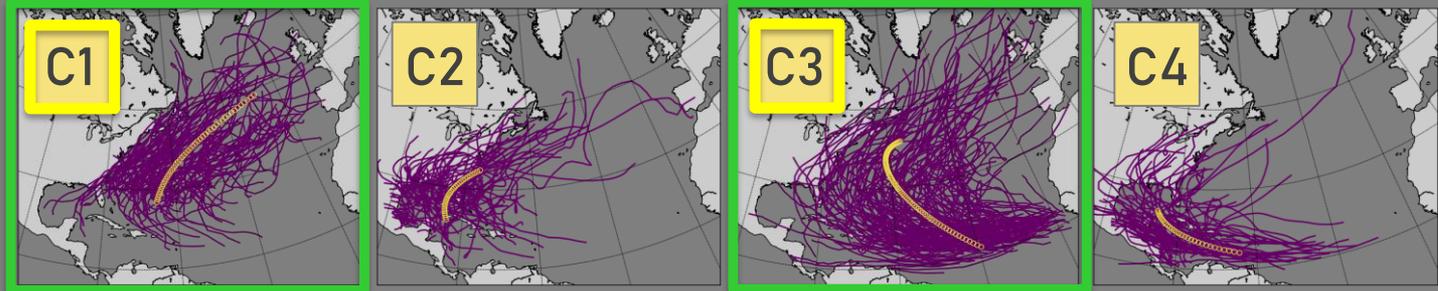


WNP

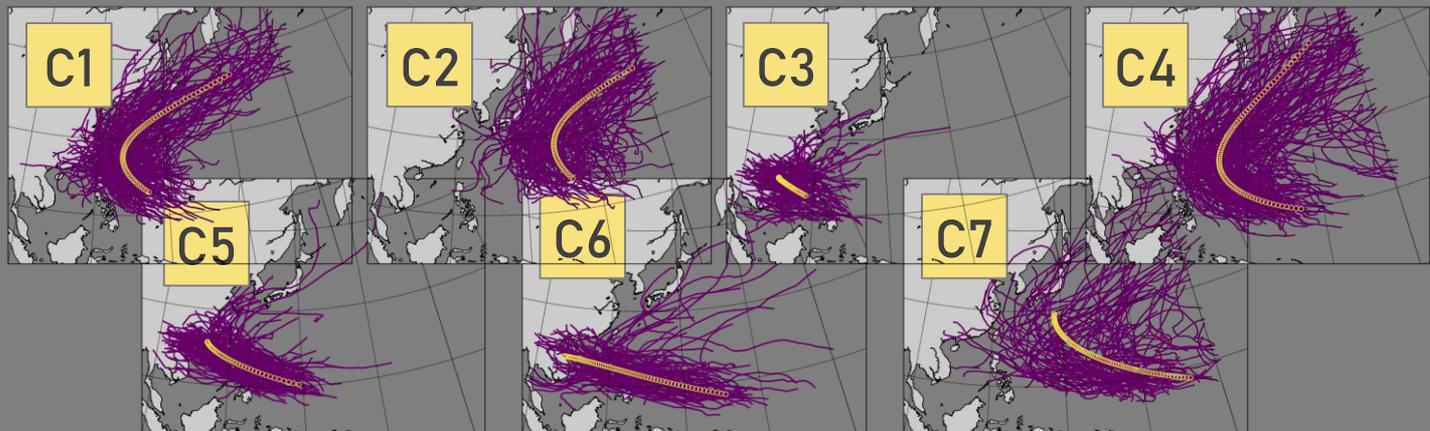


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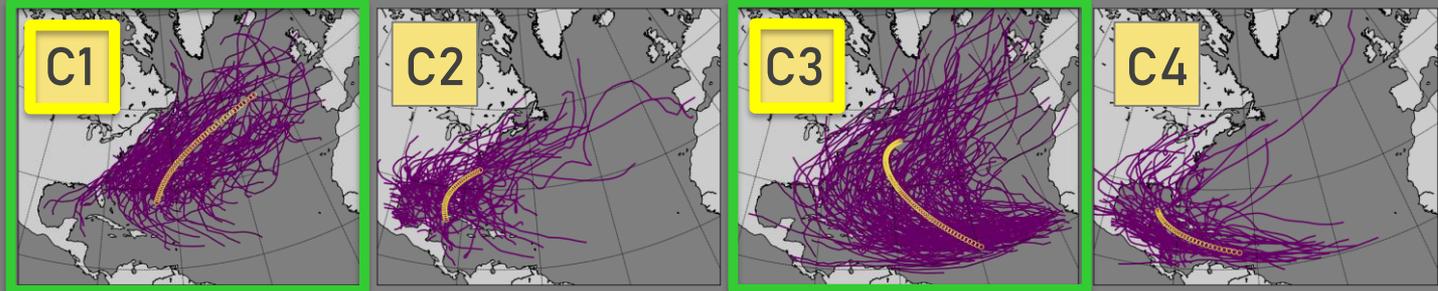


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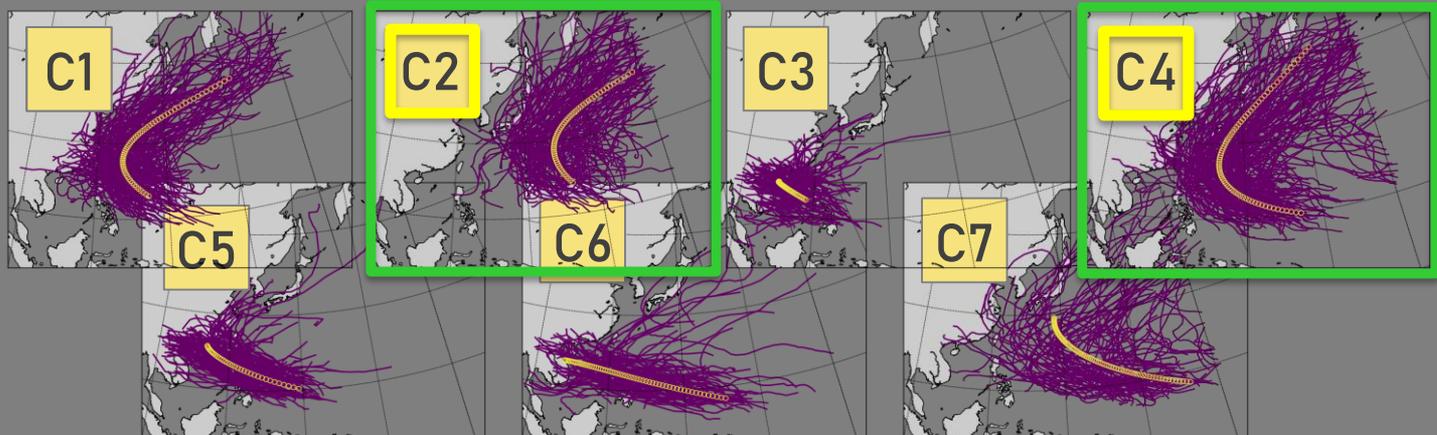


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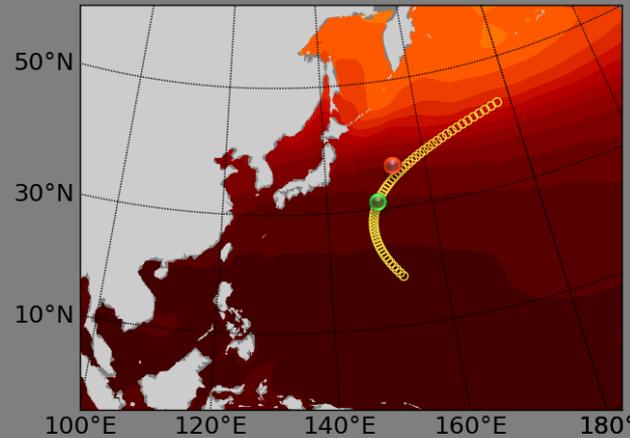


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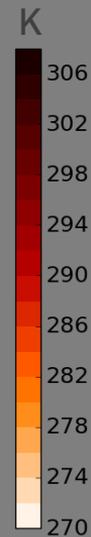
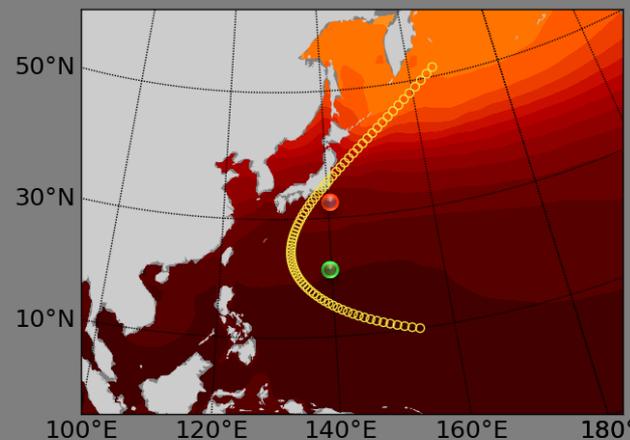


Cluster Analysis: WNP

C2



C4



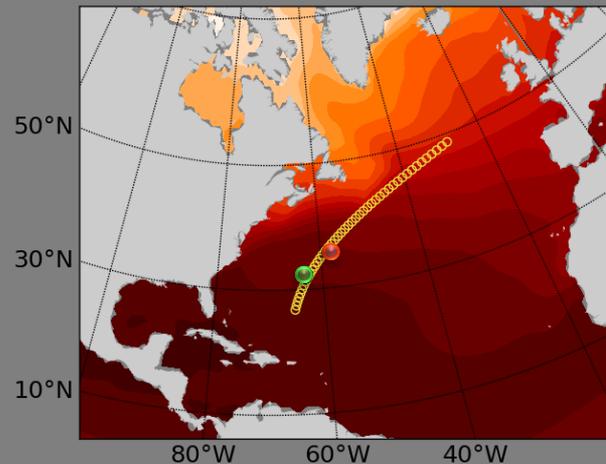
ET Pathways*

| | C2 | C4 |
|--------|-----|-----|
| B → VT | 49% | 77% |
| VT → B | 35% | 18% |
| direct | 15% | 5% |

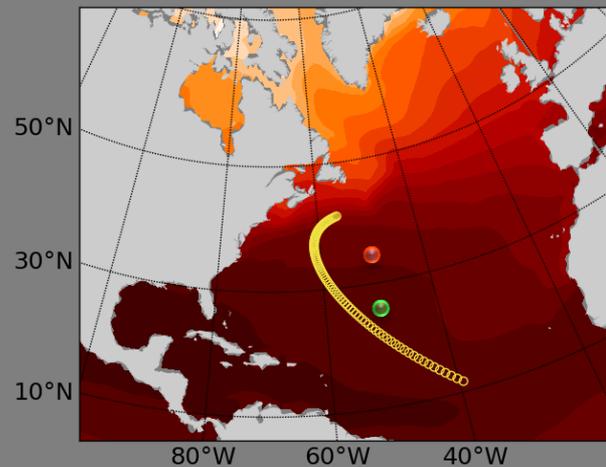
* averages of JRA-55 and ERA-Interim

Cluster Analysis: NAT

C1



C3



ET Pathways*

| | C1 | C3 |
|--------|-----|-----|
| B → VT | 35% | 59% |
| VT → B | 44% | 34% |
| direct | 21% | 7% |

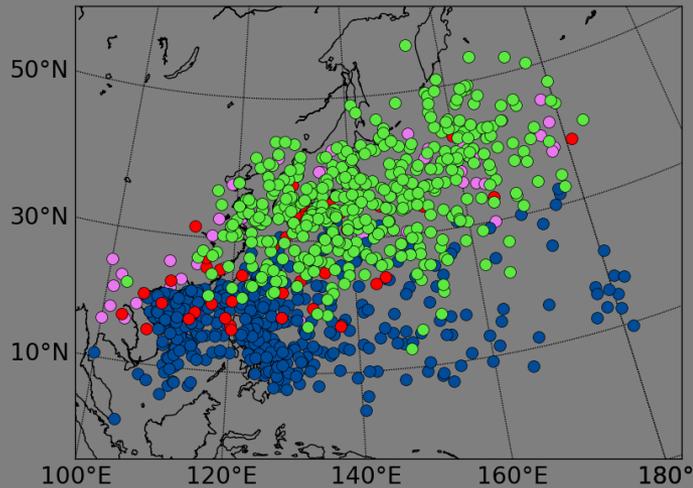
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Storm-by-Storm Evaluation

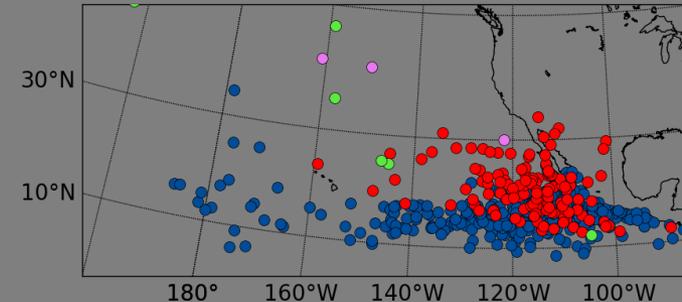
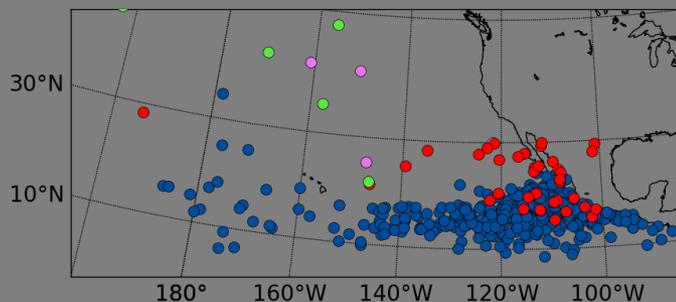
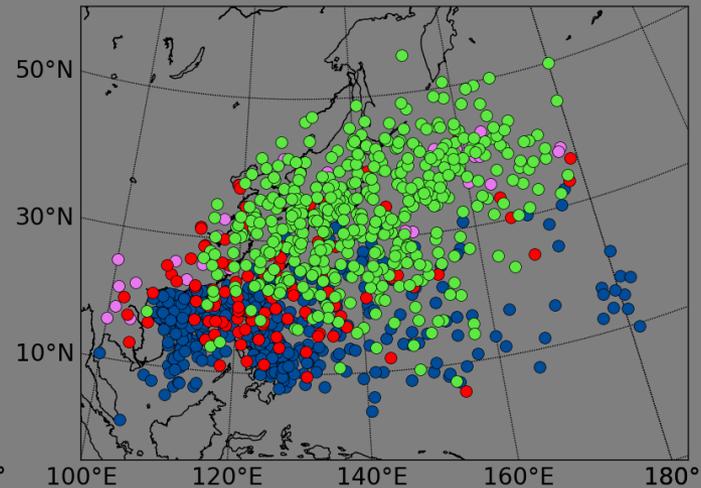
positive: ET
negative: not ET

- True positive
- True negative
- False positive
- False negative

JRA-55



ERA-Interim



Statistical Performance Measures

$$F1 = 2 \frac{\textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}}, \quad \textit{precision} = \frac{TP}{TP + FP}, \quad \textit{recall} = \frac{TP}{TP + FN}$$

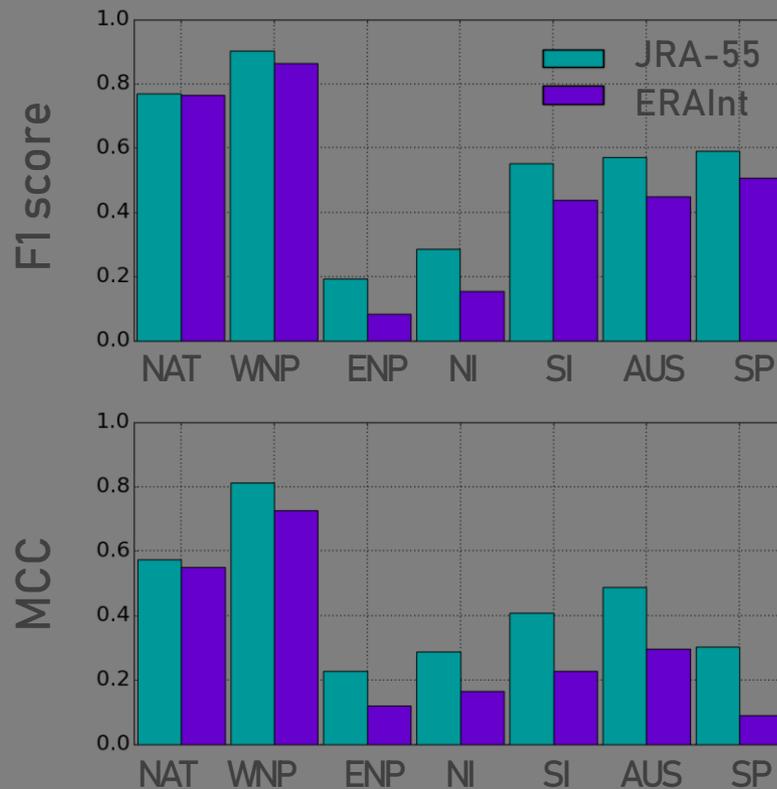
$$F1 \in [0, 1]$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$MCC \in [-1, 1]$$

- F1 score (F1) and Matthews correlation coefficient (MCC): Performance measures of CPS classification into “ET storms” and “non-ET storms”, calculated by comparing with “true” best-track classification.
- Take into account the number of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN).

Statistical Performance



- Highest scores in WNP and NAT
- Lower scores in other basins, but higher for JRA-55 classifier
- Reason (?): Artificial wind profiles in JRA-55

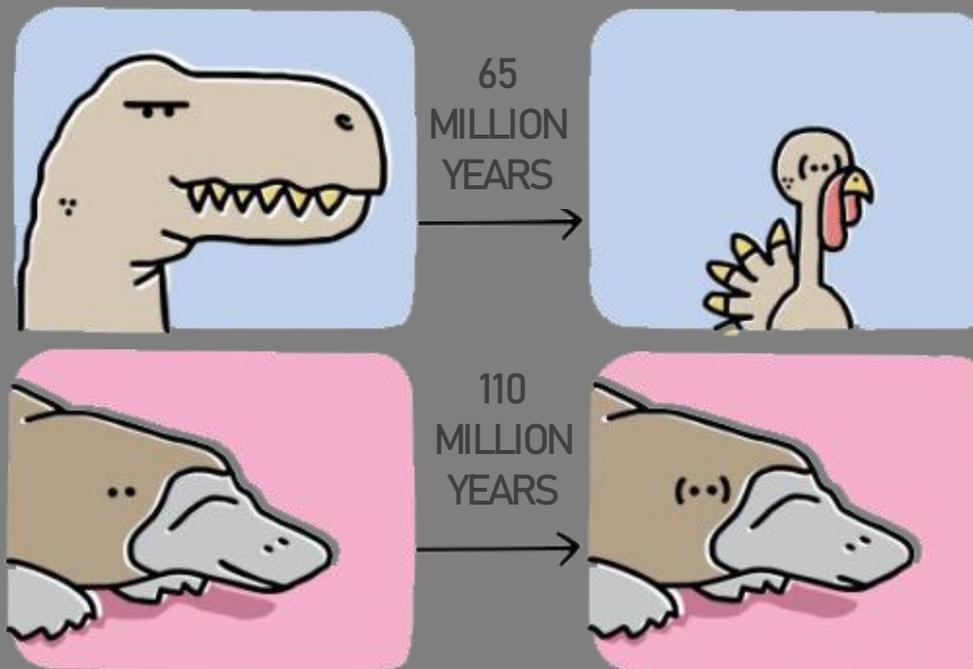
ET Climatology: One-Slide Summary

- **Method:**
Objective detection of ET using Cyclone Phase Space (CPS), from JRA-55 and ERA-Interim, 1979-2017
- **Global ET climatology**
 - ET fractions: about 50% in WNP and NAT, 45% in SP, rare in NI and ENP
 - Seasonal cycles in NH: peaks in early and late season; flatter in SH
 - Different pathways: Warmer SST goes along with more B \rightarrow V_T ETs
- **Evaluation:**
 - CPS classification agrees best with subjectively assigned best-track labels in the WNP (MCC > 0.7) and the NAT (MCC \approx 0.6)
 - JRA-55 classifier achieves higher performance scores than ERA-Interim
 - ERA-Interim classifier has a higher false alarm rate
 - Caveat: Quality of best-tracks



Predicting ET Using Statistical Learning

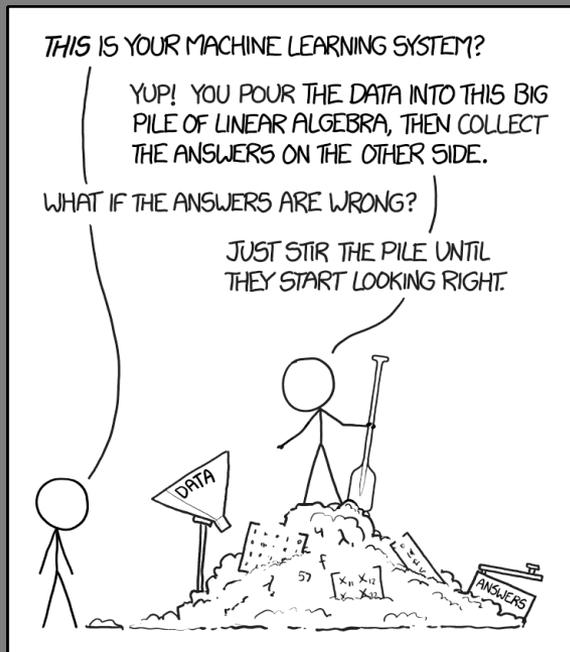
Motivation



Individual characteristics + environmental conditions → Transition?

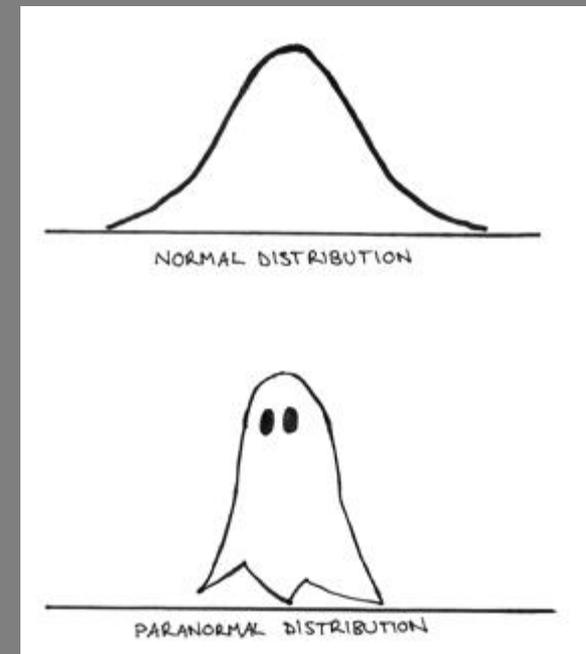
Machine Learning vs. Statistics

Machine Learning

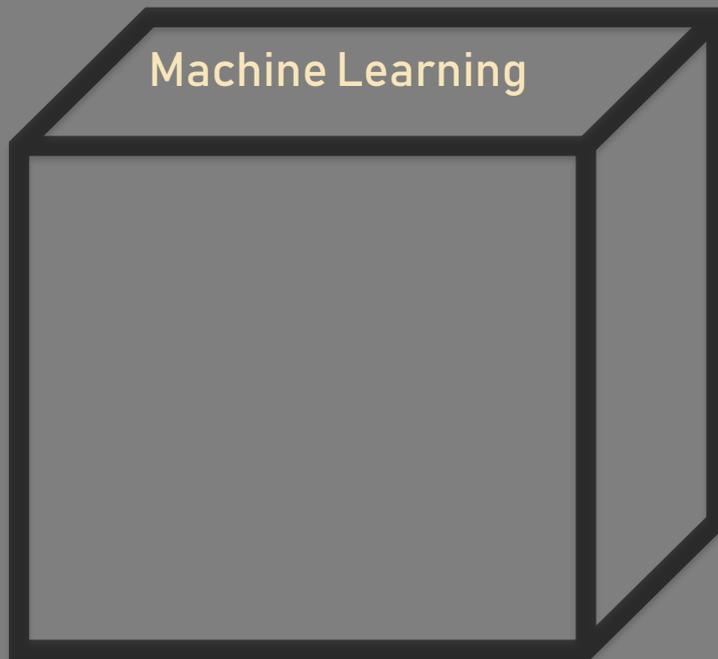


VS.

Traditional Statistics



Machine Learning vs. Statistics



Machine Learning vs. Statistics

Machine Learning

- Branch of AI

Traditional Statistics

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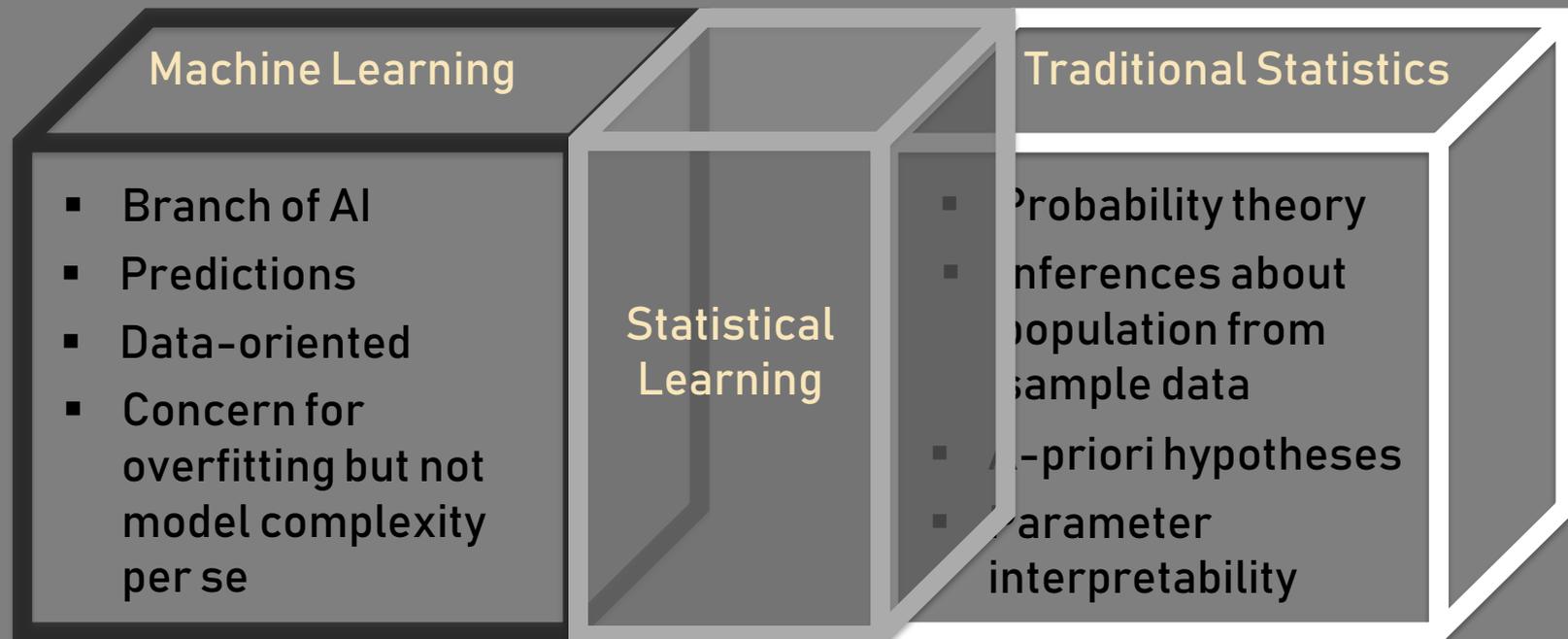
Machine Learning

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Traditional Statistics

- Probability theory
- Inferences about population from sample data
- A-priori hypotheses
- Parameter interpretability

Machine Learning vs. Statistics





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Given a set of features describing the cyclone and its environment, can a statistical model...



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Given a set of features describing the cyclone and its environment, can a statistical model...

- ... assess the relative importance of different features for a cyclone's probability of being / becoming extratropical?
- ... predict if the cyclone will be tropical or extratropical at lead times of 24h, 48h, etc.?



The Gray Box: Logistic Regression with Lasso



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Goal: Assign a data sample x to class 1 (EX) or 0 (not EX)

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$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}$$

$$x = \begin{bmatrix} 1 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$$

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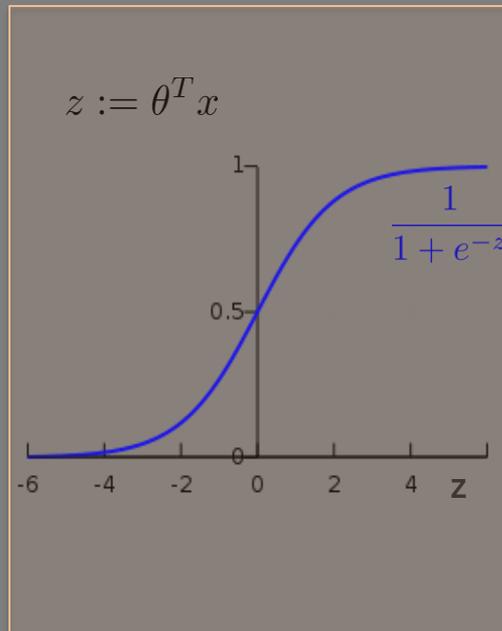
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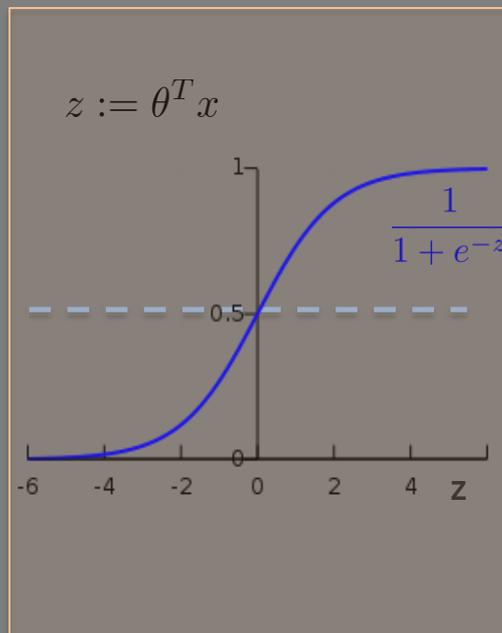
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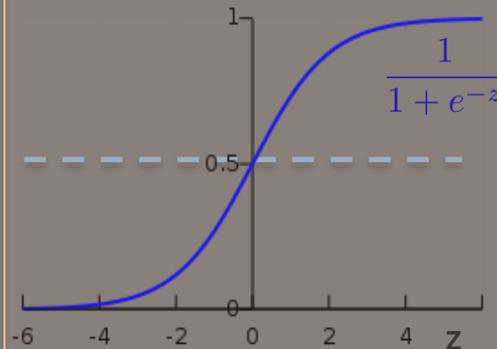
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weights,
coefficients

$$x = \begin{bmatrix} 1 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$$

features

$$z := \theta^T x$$



Interpret:

$$h_{\theta}(x) = P(\text{class 1} | x)$$

Predict:

$$1, h_{\theta}(x) \geq 0.5$$

$$0, h_{\theta}(x) < 0.5$$



The Gray Box: Logistic Regression with Lasso



The Gray Box: Logistic Regression with **Lasso**

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Goal: Prevent overfitting and select features

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Regularization using L1 norm
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Minimize cost under a constraint

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Goal: Prevent overfitting and select features

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Regularization using L1 norm
- In general: Get θ_i by minimizing a cost function (log entropy)
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Minimize cost under a constraint

$$J(\theta) = \frac{1}{m} \sum_{i=0}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

The Gray Box: Logistic Regression with **Lasso**

Goal: Prevent overfitting and select features

- “Lasso” :
Regularization using L1 norm
- In general: Get θ_i by minimizing a cost function (log entropy)
- Regularization:
Minimize cost under a constraint

$$J(\theta) = \frac{1}{m} \sum_{i=0}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)}) + \lambda \sum_{i=1}^m |\theta_i|$$

regularization

The Gray Box: Logistic Regression with **Lasso**

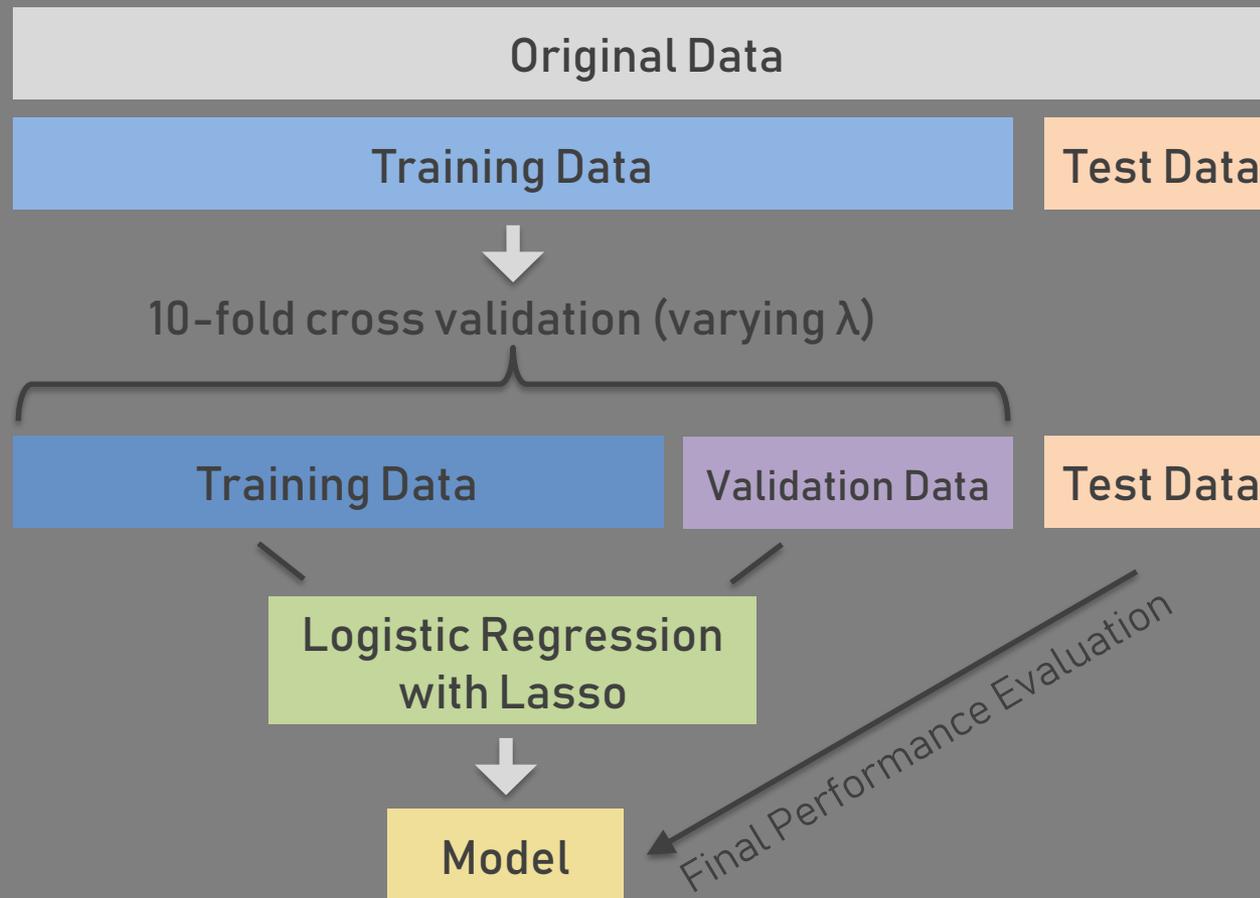
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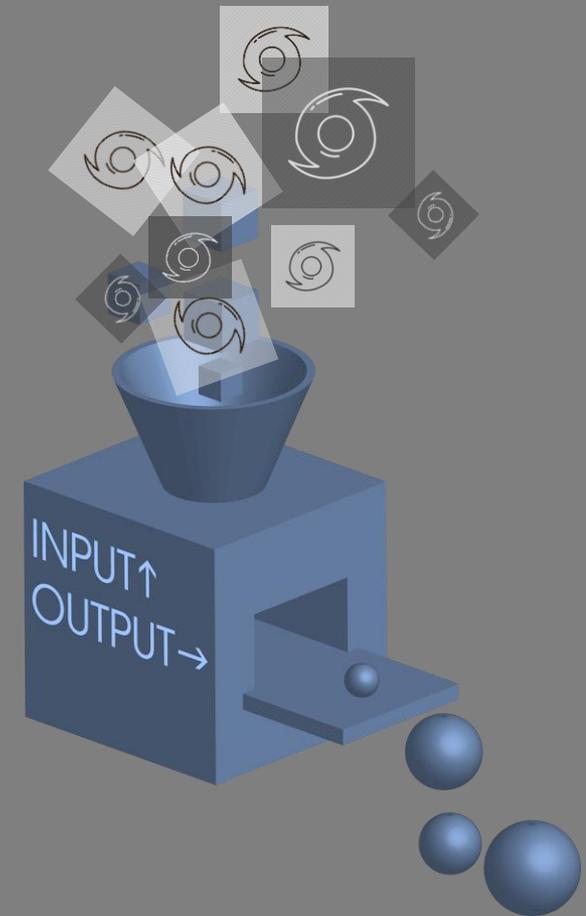
Advantage of L1 regularization:
Doesn't just help avoid overfitting, but also produces sparse solutions
(→ built-in feature selection)

Model Overview



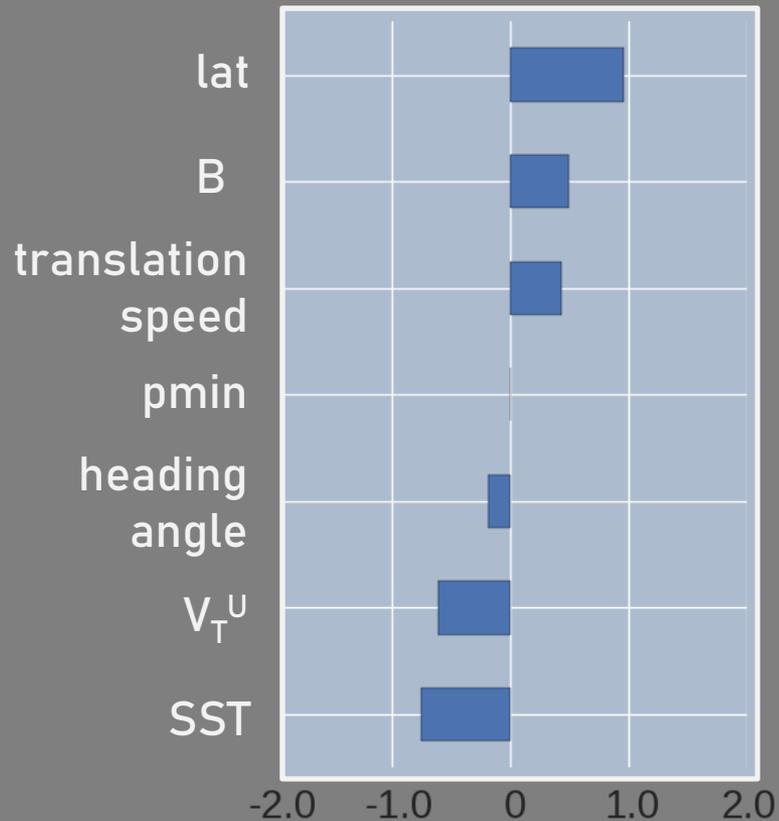
Input

- Two models:
 - Western North Pacific (WNP)
 - North Atlantic (NAT)
- Six-hourly features from
 - Best track data
 - Reanalysis data (JRA-55)
- Predictand ('EX' status at $t_0 + 24h$, $t_0 + 48h$, etc.) from best track data

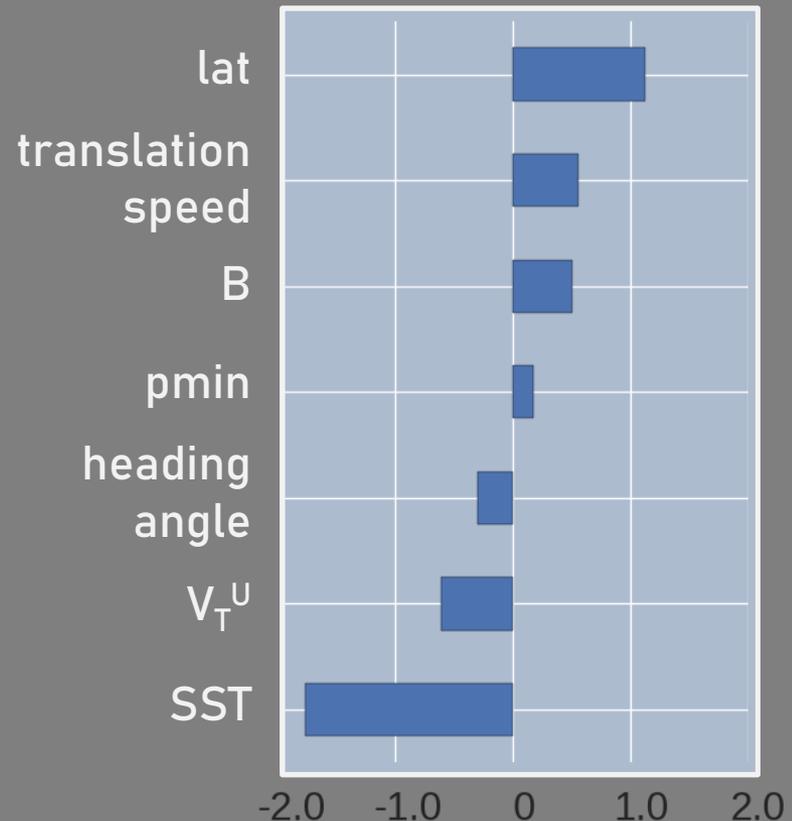


Feature Weights

NAT, lead time: 24h



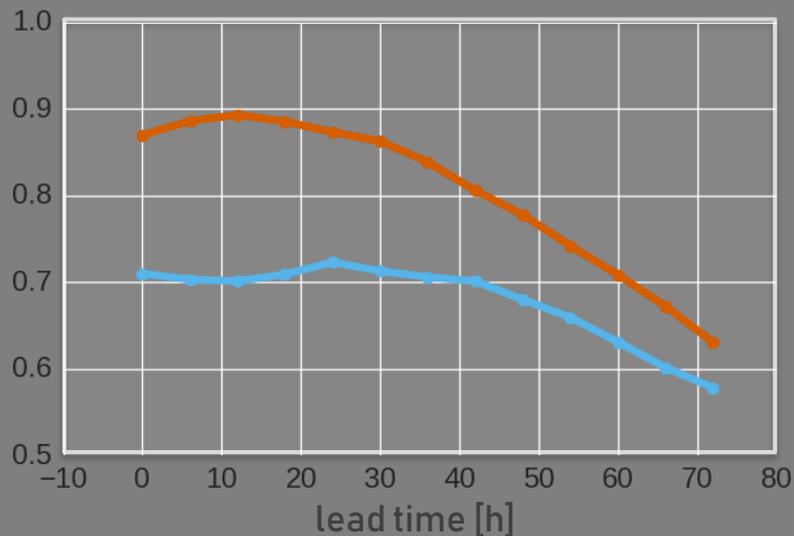
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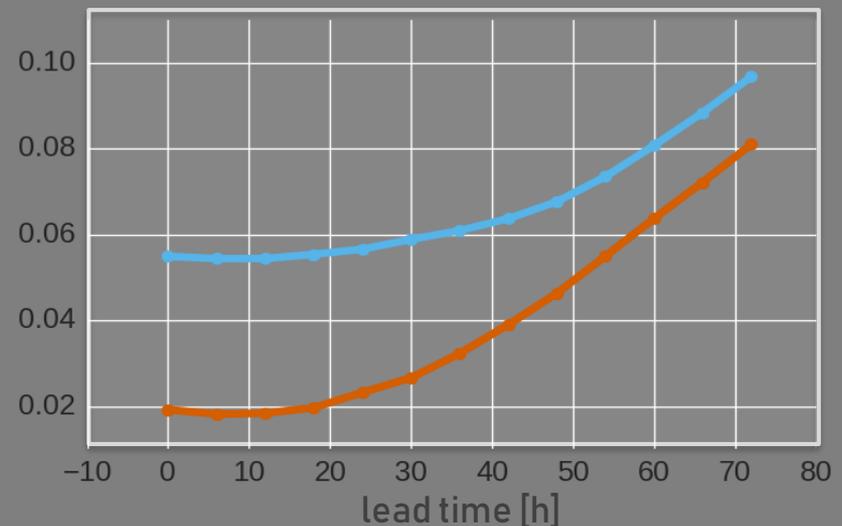
Performance on Test Set

— WNP
— NAT

Matthews Correlation Coefficient



Brier Score Loss



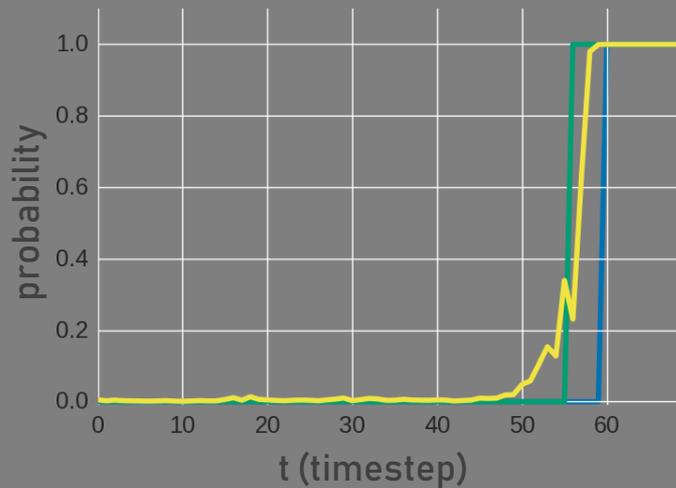
$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$\text{BSL} = \frac{1}{m} \sum_{i=1}^m \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^2$$

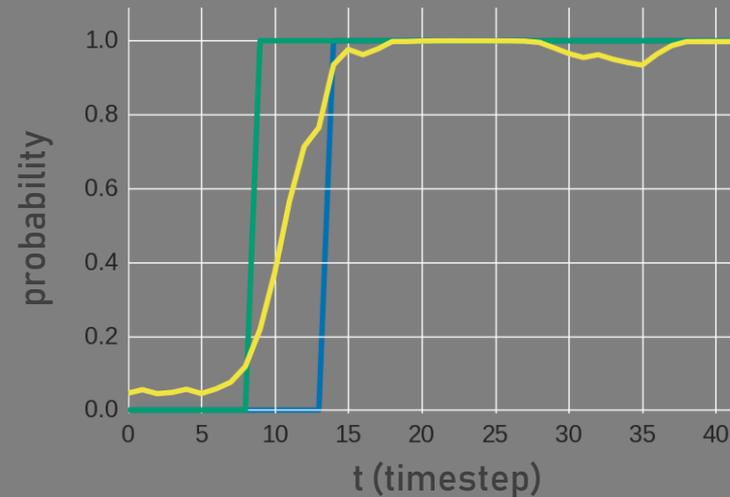
“Case Studies” on Test Set

- predicted $P('EX')$ at time $t+24h$
- true 'EX' status at time t
- true 'EX' status at time $t+24h$

Dolphin (2015)



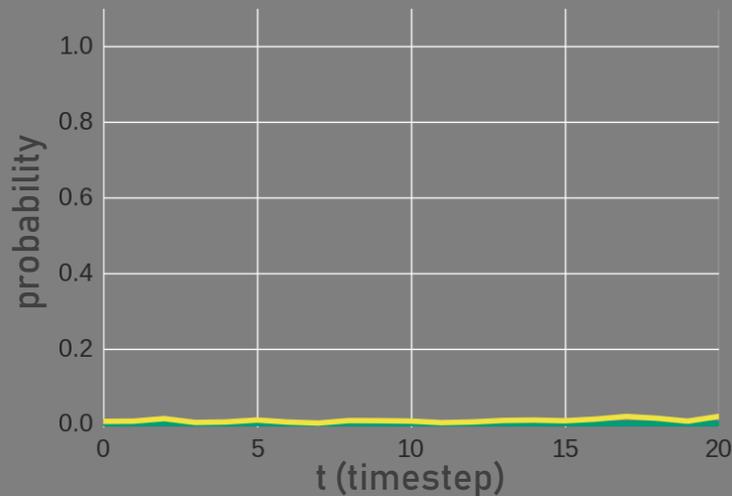
Josephine (1996)



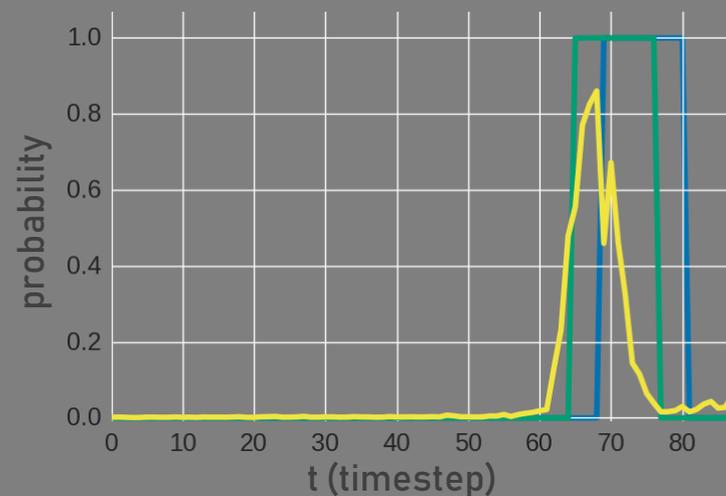
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Lois (1995)



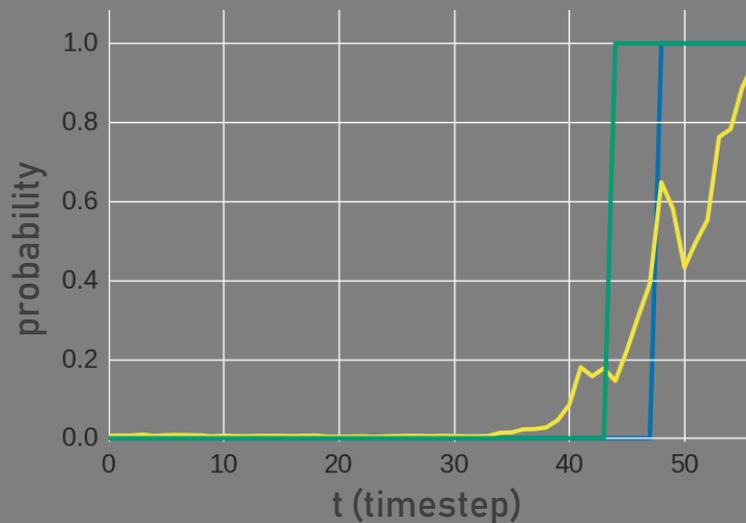
Ivan (2004)



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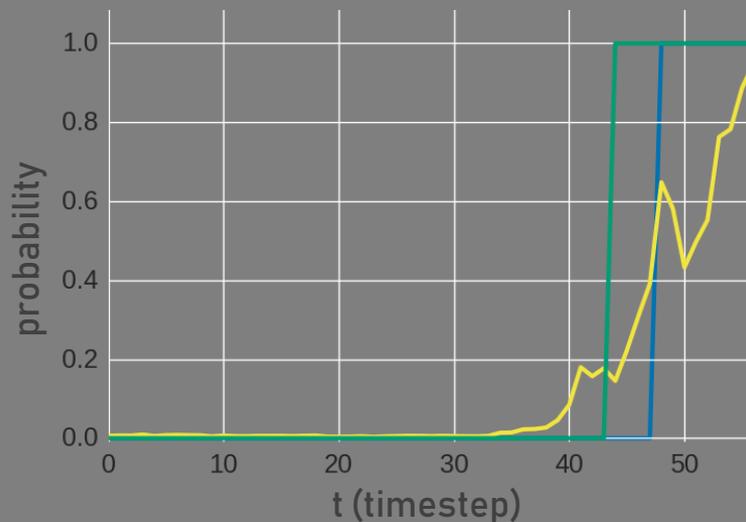
Helene (2006)



“Case Studies” on Test Set

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Helene (2006)



Final NHC Discussion on Sep 24 2006

The wind field is expanding as is typical of an extratropical cyclone. Microwave data and model analyses is showing a warm core...we believe this is due to a **warm seclusion** that is common in strong extratropical cyclones. Based on the above analyses...the **extratropical transition is considered complete**.

ET Prediction: One-Slide Summary

- **Method:**
 - Logistic regression with Lasso
 - 6-hourly input features: lat, translation speed, CPS parameters, SST, heading angle, pmin
 - Predictand: 'EX' status at t_0+24h , t_0+48h , etc.
- **Data:**

Best-track TC data from the NAT and the WNP, JRA-55 reanalysis for environmental fields
- **Feature weights:**

Lat and SST are most important predictors at lead time of 24 h
- **Performance:**
 - **It works!**
 - Metrics: Matthews Correlation Coefficient, Brier Score Loss
 - Model has skill in predicting ET at lead times up to 72 h
 - WNP model better than NAT model



Thank you!